Robust Estimation of Respiratory Frequency from Exercise ECGs

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Abstract

A method for robustly estimating the respiratory frequency from exercise ECGs is presented. The special characteristics of these recordings, such as the highly non-stationary noise, the exercise-induced QRS morphologic variations, and the dynamic nature of the respiratory frequency during the exercise test, make the classical estimation of a respiratory signal to break down. Our method is based on least-squares estimation of the rotation angles of the heart electrical axis by aligning successive QRS-VCG loops to an adaptively updated reference loop. The respiratory frequency is estimated by spectral analysis of the series of rotation angles using a reference frequency tracking algorithm. The method was evaluated by means of a simulation study. The respiratory frequency estimation error achieved by this method (0.623%±0.316%, mean±SD) was found to be lower than that obtained by a classical method based on QRS areas (3.220%±3.873%).

1. Introduction

The respiratory signal is usually recorded by means of techniques like spirometry or plethysmography. Sometimes the recording of the respiratory signal is impractical and uncomfortable for the patient, e.g. during exercise testing, since the patient is constantly moving and with an increasing oxygen demand rate. In these situations, the use of methods for indirectly extracting respiratory information, such as the respiratory frequency, are challenging.

Respiration activity influences electrocardiographic measurements. During the respiratory cycle, chest and heart movements cause a change of the electrical axis of the heart which affects QRS morphology. Several studies have developed signal processing techniques to derive the respiratory signal from the ECG, called the ECG-derived respiration (EDR) signal. Unfortunately, exercise ECGs are highly non-stationary and noisy, causing classical EDR methods to fail. Moreover, the respiratory frequency during an exercise test is in itself a highly dynamic quantity.

A method for estimating the respiratory frequency from the VCG was described in [1]. The method is based on least-squares estimation of the rotation angles of the heart electrical axis during the respiratory cycle by aligning successive QRS-VCG loops to a reference loop with respect to the transformations of rotation and time synchronization. The respiratory frequency was estimated by power spectral analysis of the estimated rotation angle series.

The aim of our work was to obtain a robust estimation of the respiratory frequency from exercise ECGs. The method in [1] was modified to better account for the special characteristics of exercise ECGs, including an adaptive reference loop to compensate for exercise-induced QRS morphologic changes and the rejection of inaccurate rotation angles due to noise and ectopic beats. For comparison, a classical EDR method based on QRS areas was also implemented [2].

2. Materials and methods

2.1. Database

At the University Hospital 'Lozano Blesa' of Zaragoza, Spain, the ECGs of 844 patients and 66 asymptomatic volunteers were recorded during a treadmill exercise test. Standard leads (V1, V3-V6, I, II, III, aVR, aVL and aVF) and RV4 were digitized at a sampling rate of 1 kHz and a resolution of 0.6 μV.

2.2. Respiratory frequency estimation

The method for estimating respiratory frequency is divided into three stages: first, a *signal preprocessing* is needed to ensure the proper performance of the *EDR algorithms* implemented in the second stage; finally, the respiratory frequency is estimated by *spectral analysis* of the EDR signals.

2.2.1 Signal preprocessing

QRS complexes are detected by the method proposed in [3], using RV4, V4 and V5. A VCG signal is synthesized from the 12-lead recorded signal using the same methodology as the one producing the inverse Dower transformation [4], but here accounting for the spatial location of RV4 rather than the standard V2 [5].

Exercise ECGs usually present large baseline drift, implying different reference voltages of successive QRS complexes. Baseline drift is attenuated using *cubic splines* interpolation.

2.2.2 EDR algorithms

QRS-VCG loop alignment

The EDR signal is given by the series of least-squares estimated rotation angles of the cardiac electrical axis between an observed and an adaptively updated reference loop. The method consists of the minimization of the normalized distance ε between a reference loop ($3\times N$ matrix $\mathbf{Y_R}$) and an observed loop ($3\times(N+2\Delta)$ matrix $\mathbf{Y}$), with respect to the transformations of rotation (3×3 matrix $\mathbf{Q}$) and time synchronization ($(N+2\Delta)\times N$ matrix $\mathbf{J}_\tau$) [6]:

$$\varepsilon = \frac{\|\mathbf{Y_R} - \mathbf{Q}^T\mathbf{Y}\mathbf{J}_\tau\|_F^2}{\|\mathbf{Q}^T\mathbf{Y}\mathbf{J}_\tau\|_F^2} \tag{1}$$

$$\mathbf{Q} = \begin{bmatrix} * & \sin\phi_z\cos\phi_y & \sin\phi_y \\ * & * & \sin\phi_x\cos\phi_y \\ * & * & * \end{bmatrix} \tag{2}$$

$$\mathbf{J}_\tau = \begin{bmatrix} \mathbf{0}_{\mathbf{\Delta}+\tau} \\ \mathbf{I} \\ \mathbf{0}_{\mathbf{\Delta}-\tau} \end{bmatrix} \tag{3}$$

where N is the number of samples of the QRS complex analysis window (80 ms). The parameter Δ denotes the number of symmetrically augmented samples to allow time synchronization (10 ms) with $\tau = -\Delta, \ldots, \Delta$ incremented in steps of 1 ms.

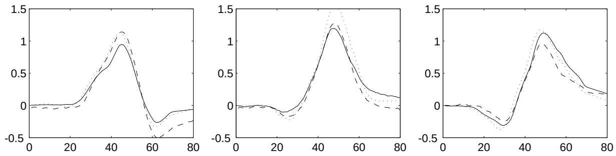
Vectorcardiographic loop alignment is performed over the early part of the QRS complex (from 60 ms before to 20 ms after the QRS fiducial point) since the terminal part of the QRS is affected by exercise-induced ST changes.

The rotation angles ϕ_x, ϕ_y and ϕ_z are computed from the estimated rotation matrix $\hat{\mathbf{Q}}$. For successive beats with similar morphologies $\mathbf{Q}$ is diagonally dominant. However, at high noise levels or in the presence of ectopic beats $\hat{\mathbf{Q}}$ does not always have that structure, leading to outlier angle estimates. In [6] it was proposed to estimate $\hat{\mathbf{Q}}_\tau$ for different values of τ, to discard non-diagonally dominant matrices and to choose that $\hat{\mathbf{Q}}_\tau$ of the remaining matrices which minimizes the criterion. When no diagonally dominant matrix $\hat{\mathbf{Q}}_\tau$ is found for any τ ($-\Delta \leq \tau \leq \Delta$) no rotation angles are estimated for that loop, leading to angle trends with large gaps in noisy periods.

The QRS morphology may change during exercise. An exponentially updated reference loop is considered to reduce the influence of exercise-induced QRS morphologic variations on angle estimations.

$$\mathbf{Y_R}(k+1) = \alpha\mathbf{Y_R}(k) + (1-\alpha)\mathbf{Y}(k+1) \tag{4}$$

The parameter α should be carefully chosen to follow exercise-induced QRS morphologic variations while avoiding adaptation to noise; a value of 0.8 was used in this study based on experimentation on actual recordings. Loops for which no diagonally dominant $\hat{\mathbf{Q}}_\tau$ is found do not participate in the adaptation of $\mathbf{Y_R}$. Fig. 1 displays $\mathbf{Y_R}$ at the beginning, at exercise peak, and at the end of an exercise ECG.



(a) Lead X **(b)** Lead Y **(c)** Lead Z

Figure 1. Reference loop (mV) at the beginning (solid), at exercise peak (dashed) and at the end (dotted) of an exercise ECG.

QRS areas

For comparison, the EDR method described in [2] was implemented. The ratio of the QRS areas over a fixed time interval of two orthogonal leads is used to define an angle θ resembling the instantaneous direction of the cardiac electrical axis in relation to one of the leads:

$$\theta_{xy} = arctan(A_y/A_x)$$
$$\theta_{xz} = arctan(A_z/A_x)$$
$$\theta_{yz} = arctan(A_z/A_y)$$

where $A_{x,y,z}$ represents the QRS area over the same interval defined for QRS-VCG loop alignment, computed by the trapezoidal method in leads X, Y and Z, respectively. The variations of the estimated $\hat{\theta}_{xy}$, $\hat{\theta}_{xz}$ and $\hat{\theta}_{yz}$ trends are used as EDR signals.

2.2.3 Spectral analysis

The respiratory frequency is estimated as the peak frequency of the EDR signal. Spectral analysis is performed by means of Lomb's method [7] since the angle trends are unequally spaced and present large gaps in noisy periods. Simple interpolation would introduce low frequencies in the spectrum which would mask the respiratory frequency.

The respiratory frequency is estimated on the moving-average of 6 spectra, each of which estimated on a 20-beat period sliding 5 beats each time. Spectral averaging is necessary to smooth frequency peaks due to inaccurate angle estimates and to enhance the peak of the respiratory frequency. The averaging window length should be chosen to allow the estimation of the lowest reasonable respiratory frequency (0.2 Hz) and to follow respiratory frequency variations during exercise. The normalized spectra of the three estimated angle trends are summed, prior to the spectral averaging, to account for electrical axis rotation projections on any lead.

To reduce the risk of spurious peak selection, the search of the largest spectral peak ($\hat{f}(k)$) is restricted to the interval [$0.7f_R(k)$,$1.3f_R(k)$] around a reference frequency ($f_R(k)$), aimed to be the smoothed running respiratory frequency, exponentially updated.

$$f_R(k+1) = \alpha f_R(k) + (1-\alpha)\hat{f}(k+1) \quad (5)$$

where k denotes the index of each averaged spectrum. The parameter α was set to 0.9 in a compromise between obtaining a stable estimation of the respiratory frequency and following its variations during an exercise test.

2.3. Simulation study

The database described in Section 2.1 does not contain simultaneously recorded respiratory signals. Therefore, a simulation study is designed to evaluate the method. First, a *noise free* exercise ECG is simulated from a set of 15 weighted averaged beats extracted from resting, exercise and recovery phases of a real exercise ECG from the database, following different ST/HR patterns [8].

The simulated records have a standard 12-lead configuration like those in Section 2.1. A VCG signal is synthesized as explained in Section 2.2.1.

The changes in the electrical axis of the heart due to respiration are simulated as described in [9]. The VCG is transformed by a rotation matrix of time-varying angles. The angular variation around each lead is simulated by two sigmoidal functions reflecting inhalation and exhalation, with a maximum variation of 5 degrees. The simulated respiratory frequency follows a pattern which often occurs during exercise (Fig. 2).

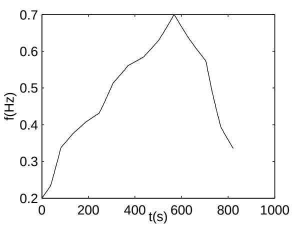


Figure 2. Simulated respiratory frequency pattern

In order to take the presence of noise in exercise ECGs into account, an additive noise model is used. Noise records are estimated as the residual of raw exercise ECGs and the corresponding averaged beat series. Spike-like QRS residuals are rejected based on a median absolute deviation (MAD) method as in [8].

In Fig. 3 a simulated record is shown during different stages of an exercise test.

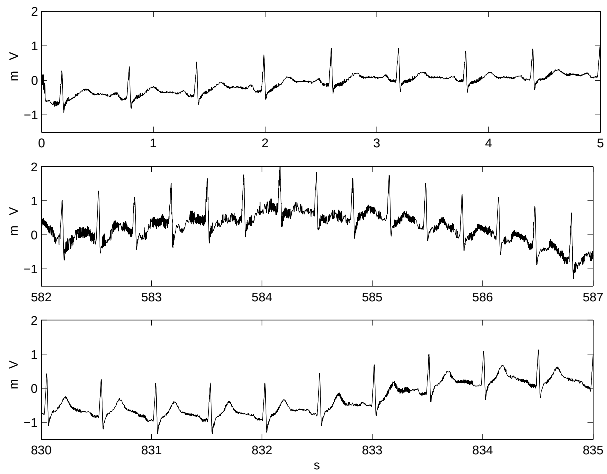


Figure 3. Simulated record at the beginning (top), exercise peak (middle), and end (bottom) of the exercise test.

3. Results

The method was evaluated on a total of 136 simulated exercise VCGs resulting from the combination of 102 noise records (mean RMS level of 444 μV with standard deviation (SD) of 267 μV) and 4 different ST/HR patterns.

An absolute error trend was defined as $\Delta f(k) = |f(k) - \hat{f}(k)|$ where $f(k)$ is the simulated respiratory frequency (Fig. 2) and $\hat{f}(k)$ the frequency estimated on each averaged spectrum k. The relative error trend was defined as $\Delta f_{\%}(k) = \frac{|f(k)-\hat{f}(k)|}{f(k)} \times 100(\%)$. The intra-subject error was characterized by the mean of $\Delta f(k)$ and $\Delta f_{\%}(k)$. Mean and SD of the intra-subject error achieved by the two EDR algorithms (QRS-VCG loop alignment, e_L, and QRS areas, e_A) are shown in Table 1 for the total number of simulated recordings.

Table 1. Mean and SD of the intra-subject error

	mean	SD
e_L (Hz)	0.0032	0.0019
%	0.623	0.316
$e_A(Hz)$	0.0171	0.0218
%	3.220	3.873

The mean and SD of the respiratory frequency estimated by both EDR algorithms during the whole exercise test can be observed in Fig. 4.

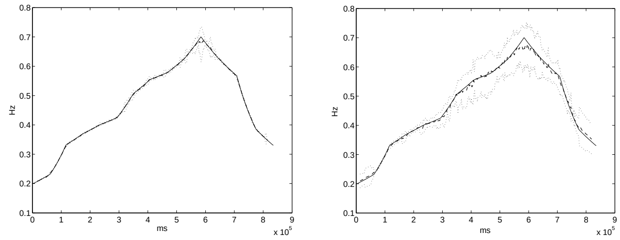


Figure 4. Mean (dashed) and SD (dotted) of the exercise test respiratory frequency estimated by the QRS-VCG loop alignment (left) and the QRS areas (right) approach compared with the simulated respiratory frequency (solid).

4. Discussion and conclusions

The idea of using the QRS-VCG loop alignment approach for estimating the respiratory frequency from the ECG was proposed in [1] and applied to a database of young non-pathologic subjects. This work extends the method in [1] handling exercise ECGs, where respiratory frequency is not constant but varying with work load, the signal is often contaminated with high levels of noise, artifacts and the presence of ectopic beats. The main modifications were rejection of non-diagonally dominant rotation matrices, an adaptively updated reference loop and tracking of the respiratory frequency.

The simulation study was designed to mimic exercise ECGs. Different ST/HR patterns typical for ischemic and healthy subjects were simulated. Performance was similar among the different patterns for both the QRS-VCG loop alignment and the QRS area approaches, so all simulated recordings were treated together to quantify the results.

The performances of the methods based on QRS-VCG loop alignment and QRS area were compared by means of the intra-subject error of the respiratory frequency estimation. Signal preprocessing and spectral analysis of the estimated rotation angle trends were identical for both approaches. QRS-VCG loop alignment approach yielded a lower error than the QRS area method (0.623%$\pm$0.316 vs. 3.220%$\pm$3.873%). As can be appreciated from Fig. 4, the QRS-VCG loop alignment outperforms the QRS areas especially at the exercise peak, where noise levels are at their peak. Comparison of the QRS-VCG loop alignment and the QRS area approaches may not be fair since the QRS area method is based on a simple calculation of measures extracted from two leads, therefore requiring less information and computation than the QRS-VCG loop alignment approach.

Sometimes the beginning of the recording is particularly noisy. In such situations the method failed to estimate the respiratory frequency at the beginning of the test and the error propagated to the end of the recording due to the frequency tracking algorithm. This was particularly problematic with the QRS area approach since its noise break down level was lower than for the QRS-VCG loop alignment. However, this phenomenon was also observed with the QRS-VCG loop alignment approach in actual exercise ECGs. It constitutes a major limitation of the method proposed in this work and may be alleviated with a robust initialization of the frequency tracking algorithm.

The method proposed here would be very useful to study the correlation between respiratory frequency and heart rate variability during an exercise test, which has been reported to be a potential marker of ischemia.

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